Error Covariance Estimation and Representation for Mesoscale Data Assimilation

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LONG-TERM GOALS

Explore and develop new ideas and methods for error covariance estimation and representation to improve mesoscale data assimilation and numerical weather prediction.

OBJECTIVES

Explore and develop new ways to study and estimate observation and prediction (background) error covariances, especially the non-homogenous, non-isotropic and/or flow-dependent aspects of prediction (background) error covariances. Explore new and efficient representations of the inverse covariances in the variational formulations for mesoscale data assimilation.

APPROACH

Built upon the existing spectral correlation model in the innovation method, a spline-spectral covariance model can be developed to estimate not only the background error correlation function but also the spatial variations of background error variance. The new method can be applied to innovation data collected from Navy's numerical weather prediction (NWP) systems.

The innovation method can be reformulated with a non-isotropic correlation model for high-resolution radar velocity innovation data. The method can estimate not only the mesoscale background error covariance but also the radar radial-velocity observation error variance and correlation between neighboring range gates and beams.

By using the proposed functional approach and generalized Fourier transformation, advanced mathematical formalisms can be developed to represent the inverse of the background error covariance by a differential operator, called D-operator. The D-operator can be used to improve the 3.5-dimensional variational (3.5dVar) radar data assimilation technique developed for the Navy's Coupled Ocean/Atmosphere Mesoscale Prediction System (COAMPS, Hodur 1997).

The PI, Dr. Qin Xu, is responsible to derive theoretical formalisms and design computational schemes for the proposed objectives. The radar data collections and computational algorithm are performed by project-supported research scientists at CIMMS, the University of Oklahoma. The required innovation data were collected by Drs. Edward Barker and Keith Sashegyi at NRL Monterey. The improved

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3.5dVar is applied by Dr. Alan Zhao to the NOWCAST system and COAMPS radar data assimilation at NRL Monterey.

WORK COMPLETED

A non-isotropic form of cross-covariance function between the radial component and tangential component (with respect to the radar beam direction) of background wind errors was derived. This cross-covariance function was used together with the previously derived auto-covariance function for the radial component (Xu and Gong 2003) to construct the background error covariance matrix and to analyze the vector wind field from Doppler radial-wind observations on the conical surface of radar scans. The utilities of these covariance functions for vector wind analyses were demonstrated by numerical experiments (Xu et al. 2005a).

Numerical experiments were performed to compare the D-operator filter (Xu 2005) and the NCEP recursive filter (Persur et al. 2003). Each filter was further combined with the B-spline filter (Xu et al. 2001a) to reduce the dimension of control variable space and improve the computational efficiency. In combination with the B-spline filter, the D-operator filter was found to be more efficient than the recursive filter, but the recursive filter gave a better preconditioning than the D-operator filter for the minimization. Certain relationships between multivariate error variances and between multivariate error decorrelation lengths were derived and coded with the above filters (in two different options) into the upgraded 3.5dVar radar data assimilation package.

Radial-velocity data were collected from the NSSL KOUN radar for a calm day on 9 May 2004 and from the phased array radar for a squall line on 2 June 2004. The collected data were processed through rigorous quality control to correct aliased velocities and to remove ground clutter contamination and migrating-bird contamination. Mesoscale background wind fields were provided by vector wind analyses (Xu et al. 2005a) using independent Doppler radial-wind observations from the Oklahoma City KTLX radar for the calm-day case, and by high-resolution COAMPS predictions for the squall line case. Time series of radial-velocity innovation (observation minus background) fields were computed for each case and used to estimate radar radial-velocity observation error covariance and background error covariance.

RESULTS

For the calm-day case (described in the previous section), the correlation between two time series of radial-velocity innovations at two different observation points was computed for each pair of observation points, say, $\mathbf{x}_i = (x_i, y_i)$ and $\mathbf{x}_j = (x_j, y_j)$ in the (x, y) coordinates centered at the radar. The computed innovation correlation data clouds were then binned every 0.25 km in r, every ±0.05 for $\cos\beta_-$ and $\cos\beta_+$. Here, $r = |\mathbf{x}_j - \mathbf{x}_i|$, $\beta_- = \Delta\beta_i - \Delta\beta_j$, $\beta_+ = \Delta\beta_i + \Delta\beta_j$, and $\Delta\beta_i$ (or $\Delta\beta_j$) is the angle of vector $\mathbf{x}_i$ (or $\mathbf{x}_j$) with respect to vector $\mathbf{x}_j - \mathbf{x}_i$ (measured positive counter-clockwise, see Fig. 1 of Xu and Gong 2003). Binned innovation correlation data points are plotted in Fig. 1 over the range of $0 \le r \le 50$ km for three sets of bin intervals. As shown, when r decreases to 2 km, the three sets of correlation data points converge nearly to the same vertical level. As r decreases further from 2 km toward 0, the correlation data points start to increase rapidly towards 1, but the three sets diverge first before they converge to 1 at $r = 0$. This indicates that radar observation errors become correlated as r reduces into the range of $0 \le r \le r_o = 2$ km. The innovation variance was computed at each observation point and averaged over all the observation points. The averaged innovation variance is $\sigma_d^2 = 11.26$ $m^2\ s^{-2}$ (for the calm-day case).

A two-step approach was developed to estimate the background wind error variance and correlation functions. In the first step, a quadratic form of background radial-wind error covariance function (scaled by σ_d^2) was used to fit all the binned innovation correlation data points over the limited range of $r_o < r \leq 10$ km. The fitted quadratic form converged uniformly (for all bin intervals of $\cos\beta_+$, not shown) to $\sigma^2/\sigma_d^2 = 0.58$ at $r = 0$ (shown by ♦ in Fig. 1), where σ^2 is the background wind error variance. This gave $\sigma^2 = 0.58\sigma_d^2 = 6.53\ m^2\ s^{-2}$ (for the calm-day case). In the second step, the non-isotropic form of background radial-wind error covariance function in (2.6) of Xu and Gong (2003) was scaled by σ_d^2 and then used with the truncated spectral expansions in (4.1) of Xu and Wei (2001) to fit the binned innovation correlation data points over the full range of $r_o < r \leq D = 50$ km. The error variance σ^2 estimated in the first step was used to constrain the sum of the estimated spectral coefficients, so the background wind error correlation functions were well estimated (not shown). However, if the error variance and spectral coefficients are estimated with a single-step approach by directly fitting the non-isotropic form over the full range, then the sum of the spectral coefficients will be unconstrained and yield an overestimate of σ^2/σ_d^2 (= 0.69 as shown by × in Fig. 1 for $N = 9$, where N is the truncation number for the spectral expansions).

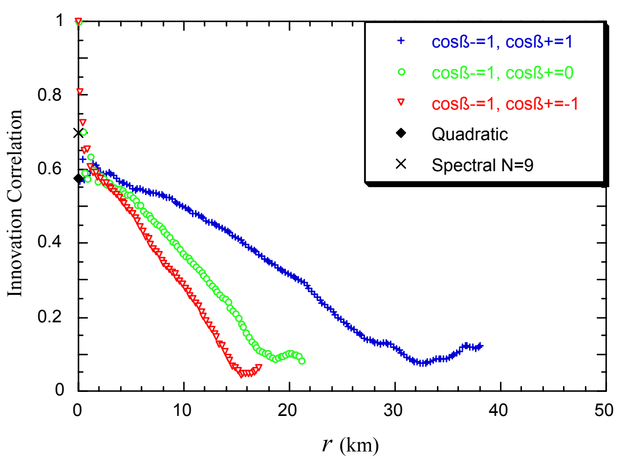

Fig. 1. Binned innovation correlation data points over the range of $0 \leq r \leq 50$ km for three sets of bin intervals in the vicinities of $\cos\beta_- = 1$ and $\cos\beta_+ = 1, 0, -1$, respectively.

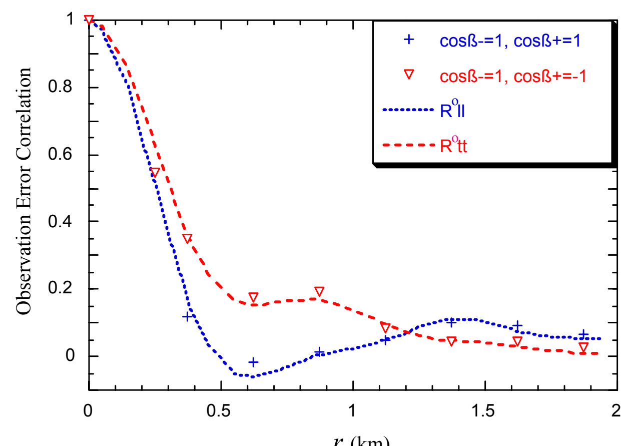

Fig. 2. Observation error correlation functions estimated from observation error correlation data points binned within $0 \leq r < r_o$ (= 2 km) for two sets of bin intervals.

After the above two steps, the observation error variance was estimated simply and yet quite reliably by $\sigma_o^2 = \sigma_d^2 - \sigma^2$ (= 4.73 $m^2\ s^{-2}$). Binned observation error correlation data points were then obtained by subtracting the estimated background error covariance (scaled by σ_d^2) from the innovation correlation for each bin box within the range of $r < r_o$ and then re-scaling the result by σ_o^2. A non-isotropic form of radial-velocity correlation function was used with spectral expansions to fit the binned observation error correlation data points over the narrow range of $0 \leq r < r_o$ (= 2 km).

As shown in Fig. 2, the estimated $R_{ll}^{o}(r)$ (blue dotted) and $R_{tt}^{o}(r)$ (red dashed) fit closely to the binned observation error correlation data points. Here, $R_{ll}^{o}(r)$ is the correlation between neighboring gates along the same radar beam, and $R_{tt}^{o}(r)$ is the correlation between neighboring beams along the same range circle. These radar radial-wind observation error correlation functions were well estimated, for the first time, by the reformulated innovation method.

The reformulated innovation method was also applied to phased array radar radial-wind observations (collected for the squall line case). With the fast phased array radar scans, radial-velocity innovation (observation minus forecast background) data can be accumulated rapidly and used nearly real time to estimate the radar observation error and background error covariances. With a proper data thinning strategy, the reformulated innovation method was able to estimate these error covariances nearly real time. The 3.5dVar radar data assimilation package was also upgraded to use the estimated error covariances. This led to an integrated approach in phased array radar data assimilation (see Xu et al. 2005b).

IMPACT/APPLICATIONS

(1) The reformulated innovation method provides an objective and statistical way to estimate radar radial-velocity observation error covariance and mesoscale background error covariance. The estimated error statistics provide useful information for radar data assimilation.

(2) The D-operator representation of error covariance improves the efficiency of the 3.5dVar radar data assimilation technique developed for COAMPS.

TRANSITIONS

The upgraded 3.5dVar radar data assimilation package was delivered to Dr. Alan Zhao at NRL Monterey for nowcast applications and COAMPS radar data assimilation (Zhao et al. 2005a,b). The reformulated new innovation method will be integrated with 3.5dVar and delivered to NRL Monterey for operational tests and applications.

RELATED PROJECTS

Radar Velocity Data Quality Controls (funded by NOAA/USWRP and NCEP to NSSL and OU).
Easy-to-Use Interface for Radar Data Quality Control and Error Estimation (funded by NOAA HPCC to NSSL and OU)

6.2 Shipboard Data Assimilation System/Doppler Radar (funded by ONR to NRL Monterey).

6.2 Data Assimilation for Mesoscale Prediction (base funding BE-435-009 to NRL Monterey).

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